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# Smartphone Accelerometer Data used for Detecting Human Emotions

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***Abstract*—The paper outlines work on the classification of emotions using smartphone accelerometer data. Such classification can be used, in conjunction with other methods of emotion detection, to adapt services to the user's emotional state. The data is collected from individuals who have been carrying their phone in a pocket while walking. An Android app was developed in order to monitor the smartphone accelerometer of the individuals who participated in the study and occasionally requested them to judge and submit their emotional state. This way, data is collected from a natural environment rather than a laboratory setting. The recorded data is then processed and used to train different classifiers to be compared. The machine learning algorithms decision tree, support vector machine and multilayer perceptron are used for this purpose. Emotions are classified in two dimensions: *pleasantness* and *arousal* (activation). While the recognition rate for the arousal dimension is promising at 75%, pleasantness is harder to predict, with a recognition rate of 51%. These findings indicate that by only analyzing accelerometer data recorded from a smartphone, it is possible to make predictions of a person's state of activation.**

## I. Introduction

Smartphones becoming more powerful are leading to the opportunity of having them becoming more intelligent as well. They contain a large number of sensors that would be able to sense various aspects of the user's behavior and mental state. However, this has only to a limited extent been explored yet. Having a system that is able to recognize the emotions of the user would be useful in many contexts like therapy and adaptive smartphone user interfaces.

However, we don't necessarily *want* the computer to know how we are feeling, because of privacy issues. On the other hand, scientific advances in artificial intelligence also bring an interest in letting emotions into the world of computing. Rosalind J. Picard writes in her book *Affective computing* [1]:

> *I have come to the conclusion that if we want computers to be genuinely intelligent, to adapt to us, and to interact naturally with us, then they will need the ability to recognize and express emotions [...]*

A major part of the field of *affective* computing consists of recognizing human emotions based on one or more types of data collected from the person whose affective state is being evaluated. This is not a question of perfect recognition of emotions, but rather a better-than-random suggestion. The prediction made by the computer can then be used to influence the behavior of a system that interacts with the human.

Smartphones may use many different ways to sense emotions, including, but not limited to physiological measurements, self-reports, phone usage, speech and facial expressions [2]. Common for most of these methods is that they either require some kind of sensor connected to the body, manual input from the user or another *intrusive* method of data collection in order to work, or they require the collection of data over a long period of time in order to predict the long-term mood of the user.

While the accuracy of such methods is frequently shown to be high, they do not allow for an instant evaluation of a person's emotions without the use of any *external* equipment. That means that the practical use is somewhat limited, and the methods cannot immediately be used by the general population. In this paper, we will address these issues by introducing a system for classifying a person's short-term emotions solely based on data from the accelerometer embedded in the person's smartphone.

Do we actually move in a different way when we are happy as opposed to when we are sad? Does it make any difference whether we are tired or energetic? Various studies indicate that such a relation might exist, both for walking and other movements [3], [4], [5]. The accelerometer allows us to capture some of this information that connects movement to emotions.

The increased computational power in smartphones make them able to perform a large number of computations in addition to just enabling us to perform simple tasks like making phone calls and sending text messages. This gives us the opportunity to record and analyze the accelerometer data without disrupting the normal use of the phone. Using machine learning for classification on user data collected through the app *Emotions*, developed for this work, we propose a way to make predictions about the emotions experienced by the user while walking, carrying the phone in a pocket. In the next section we describe some earlier related work followed by our own work in section III. Results of the experiments are reported in section IV and conclusion is given in section V.

## II. Background

The relevant background information is presented in this section. First, emotion theory is briefly outlined together with the definition of emotions that will be used in our own work.

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TABLE I: Overview of mood vs emotions

| | Mood | Emotions |
|---|---|---|
| Duration | Long-term (hours/days) | Short-term (sec./minutes) |
| Expressiveness | Lower | Higher |
| Intensity | Lower | Higher |
| Cause | Non-specific | Something specific |
| Examples | Usually generalized into positive mood and negative mood | Enjoyment, surprise, anger, fear etc. |

Then follows an overview of other related studies, and it is shown how our own work adds to the earlier work.

### A. *Emotions*

It is useful starting with a definition of *emotions*. In daily speech equivalent to feelings, they are within the field of psychology considered to have three components [6]:

- Specific feelings associated with the emotion
- Physiological changes in the person experiencing the emotion
- Inclinations to act in a specific way

This understanding of emotions obviously also includes changes in the movement patterns, which is what we are concerned with in this work. A key difference between emotions and the related concept of *mood* lies in the duration. While mood is considered long-term, emotions are typically more intense and have a duration that can be limited to only a few seconds or minutes [7], [8].

Another way to view the difference between the two concepts is to see mood as a weaker and more persistent state of affect, which generally is not clearly visible to others. Mood is typically generalized into positive and negative mood. Emotions, on the other hand, can be considered more specific, spontaneous and short-term, and they will to a greater extent be visible on the person experiencing the emotions. Examples of emotions can be *happy*, *angry* and *surprised*. The terms are closely related, however, and mood tends to affect which emotions a person will experience (and vice versa). See Table I for an overview on the two concepts.

Emotions are classified either as discrete categories of basic emotions or on axes in several dimensions [6].

*1) Discrete Categories of Emotions:* Corresponding to the common view of emotions, the discrete classification has been frequently discussed, e.g. by Ekman [9]. He defines the basic emotions *anger*, *disgust*, *enjoyment*, *fear*, *sadness* and *surprise*[1]. These emotions are very common, and most people have some kind of understanding of what they mean and how they are expressed.

Another list of emotions was compiled by Tomkins [10], defining the nine basic emotions of *interest*, *joy*, *surprise*, *distress*, *fear*, *shame*, *contempt*, *anger* and *disgust*. Tomkins' list is the basis of more recent research into the connection between emotions and neurotransmitters by Lövheim [11]; a model that is recently used in affective computing research [12], [13]. While these selections seem rather limited, they encompass a fairly high portion of the emotional states a person can experience.

[1]Ekman later adds to this, resulting in a list of 15 emotions [8]

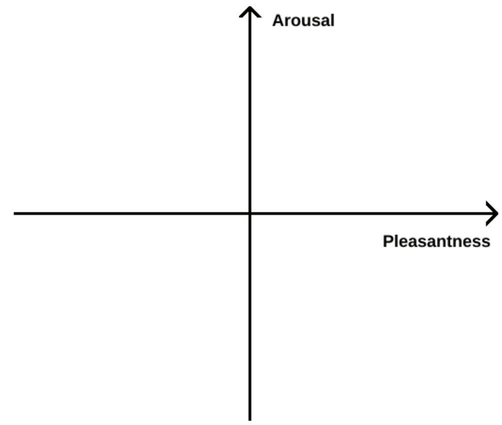



Fig. 1: A Circumplex model of affect

*2) Emotions in Two Dimensions – A Circumplex Model of Affect:* A dimensionality-based model of emotions was suggested by Russel [14]. Named *A Circumplex model of affect*, it seeks to model the different kinds of emotions on a two-dimensional chart. Figure 1 illustrates the main idea, using the two dimensions *pleasantness* and *arousal*. These two dimensions have been shown to carry the majority of the information related to the perceived difference between various emotions [15]. Each emotion will be scored on the two dimensions, e.g. *angry* might get a high score on arousal and a moderately low score on pleasantness. This way it is possible to extract common terms from the dimensional model. We use this model in our work later in this paper.

### B. *Previous Work Related to Detecting Affect*

Research has been undertaken on mood recognition as well as emotion recognition. These two terms, while frequently used interchangeably in the literature on affective computing, have different meanings, as explained in section II-A and also discussed in affective computing research [16], [21].

An overview of some relevant work can be seen in Table II. Most of the reviewed studies involve affect detection. In some of them an accelerometer or other sensors are involved, but many different sources of input are used. A study concerned with activity detection is also included, as accelerometer-based activity detection has shown high accuracy and has similar challenges when it comes to preprocessing of data.

The studies that have been described in this section generally show very promising results. Affective data has been collected by analyzing movement and various elements of smartphone usage. While these results are very interesting, there are some challenges when it comes to practical use. The following are some of the limitations amongst the mentioned studies:

- Analysis of phone usage data has to be done over a long period of time. While showing high accuracy on predict-

TABLE II: Work related to emotion detection

| Summary | Sensors | Conditions | Categories | Accuracy |
|---|---|---|---|---|
| MoodScope – mood prediction based on phone usage patterns (LiKamWa et al.) [16] | None, only phone usage data | Personal device, long term | Circumplex model | 66%–93% |
| Emotion detection taking into account user's sitting posture (Hossain et al.) [17] | Smartphone accelerometer | Controlled environment | Neutral, stressed, excited | 51%–70% |
| MoodMiner mood prediction based on sensor data and smartphone usage (Ma et al.) [18] | Smartphone gps, accelerometer and usage data | Personal device, long term | Three dimensions: displeasure, tiredness, tensity | Below 50% |
| Activity monitoring based on accelerometer data (Zhang et al.) [19] | Accelerometer in smartphone strapped to belt | Controlled environment + at the participant's workplace | Six states descriptive of activity or no activity | 63%–83% |
| Emotion detection based on bracelet-embedded accelerometer (Zhang et al.) [19] | Accelerometer worn on wrist and ankle. | Controlled environment | Angry, neutral, happy | 81% |
| Accelerometer- and pressure sensor-based emotion detection related to sitting posture (Shibata and Kijima) [20] | Accelerometers attached to multiple parts of body + pressure sensors on chair | Controlled environment | Three dimensions: pleasantness, arousal, dominance | Promising for the first two dimensions |
| Emotion prediction based on movements (Bernhard et al.) [4] | Data from motion capture (suit and cameras) | Controlled environment | Neutral, happy, angry, sad | 50%–81% |

ing a person's long-term mood, it cannot predict short-term emotions. For the purpose of mood monitoring, it is effective when looking at periods of time of at least one day, but this approach fails to give good predictions for shorter time frames.

- Studies performed in controlled environments might cause the participants to move or otherwise act differently than they do in their normal environments. Picard [1] discusses this problem and mentions e.g. the reluctance of some participants to express negative emotions in a laboratory setting.
- People generally do not want to wear extra gadgets. Requiring external sensors, e.g. accelerometers worn on specific parts of the body, or requiring that the phone is carried in a specific way, are not reasonable to expect in people's everyday life.

The work reported in this paper emphasizes on the problem of emotion classification in a more realistic way. It is reasonable to assume that most smartphone users carry their phone, usually in a pocket, when they move. If we can find a way to predict emotions solely based on how the person moves, as recorded by the smartphone-embedded accelerometer lying in a pocket, we have an approach that can be used by most smartphone users in a non-intrusive way. This increases the likelihood of finding a practical use for the gathered information.

## III. Detecting Emotions

Different ways of predicting emotions from smartphone data have been reviewed. In this work, the focus is on the movement sensors of the phone, more specifically the accelerometer. The following is an overview of our work:

- The collection and classification of the data is using the model of emotions defined by the *Circumplex model of affect* (see section II-A2). Using that model, accelerometer data has been collected together with self-reported emotions from a set of participants. Details of the data collection follow in section III-A.
- When considering how to collect data, we decided on developing an *Android app* that the participants could keep running in the background. The app would then request data when appropriate. Compared to the alternative of setting up a controlled test environment, this solution lets the participants use their own devices and allows us to record data from situations where they are not located in an artificial testing environment. This should give the study greater *ecological validity*, i.e. let the testing environment approximate the real world as much as possible, and hopefully provide data that is recorded as non-intrusively as can be expected. The specific functionality of the app is described in section III-A.
- The raw data will be filtered and segmented into steps and periods of motion. Features will be extracted from that processed data, and this is explained in sections III-B.
- Finally, classifiers will be trained on the recorded data. The experiments performed and results can be found in section IV-B.

### A. Data Collection While Moving

The phone can be in many different states of movement and usage:

1) Lying still and being used or not being used
2) Held in hand and being used while the user is stationary
3) Held in hand and being used while the user is moving
4) Being carried and not being used while the user is moving

In order to increase the chance of successful classification, this work will be limited to *one* of the mentioned situations. #1 is not relevant, as we are going to use the accelerometer for data collection, which obviously requires movement. #2 (and technically also #3) was initially tested, but due to apparent randomness in the data, we decided to postpone further testing and rather focus the project on #4. This is the basis of the functionality of the app *Emotions*, which is described below. Later it would be interesting to revisit state #2 and see whether it is possible to get any results there, as previous research has shown some potential [18].

Once the app is installed and opened, it launches a service that remains open until the app is closed by clicking the exit button. This service monitors the movements of the phone by fetching the value from the accelerometer once every second. The value is compared to the previous one, and if the difference is very small it is just counted as variation due to inaccuracies/noise in the accelerometer. A larger difference can indicate that the person is moving, and if a large difference is found in ten consecutive readings, i.e. over a period of ten seconds, it is probable that the phone is currently moving. This is one way to determine that we potentially want to make a recording, as we only want to do it when the user is walking. Once movement has been detected, the app determines whether or not to start recording according to the following criteria:

- If a recording has occurred recently (within the last ten minutes), nothing happens. Too frequent requests for information are a likely source of annoyance to the user, and that could lower the chance of getting data.
- Else the app intends to start recording and waits for two minutes. This delay is intended to handle situations where the movement is due to the user picking up the phone, puts it in a pocket and starts moving, or just puts it down again after performing some activity on the phone. Thus, a delay of two minutes increases the chance of the user actually having started walking.
- When the two minutes have passed, the app checks whether the phone is currently being used, i.e. the screen being active.
- If it is being used, nothing happens, as that could indicate that the user just picked up the phone in order to use it.
- If the phone is not currently being used, the recording of accelerometer data starts and continues for 20 seconds.

After a 20 seconds recording is finished, the app assess the jerk values for it which are calculated from the acceleration. This is in order to not use the recording if the user has not been moving all the time – indicated by a low jerk value in low activity periods. If this test indicates continuous motion, the user is notified and asked to choose *one* out of five choices for each of the two dimensions, pleasantness and arousal. The collected data is then sent to a server where the data is later going to be used for training a classifier. Such transfer of data requires the privacy of the participants to be handled in a satisfactory way. In this work, the privacy is ensured through complete anonymity of the participants. Each participant is identified only through a randomly generated id which is used to keep track of the origin of the various recordings.

### *B. Preprocessing of Data*

In order to reduce the noise, the acceleration data is first filtered with a moving average filter. For each recording, this filter is applied to each of the three raw acceleration vectors $\vec{a_x}, \vec{a_y}$ and $\vec{a_z}$, calculating each new value as the average of itself and the values directly adjacent to it. Different filters were initially tested but we ended on using the following one:

$$m = \left\{\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right\}$$

Initial experiments showed that whether the participant actually has been moving during a recording makes a significant impact on the classification results. Therefore, it was necessary to extract the periods of actual motion before extracting features. To help removing non-moving parts of a recording, the accelerometer data was segmented into (walking) steps. Parts without motion lacked step detection and could easily be removed. This represents a more thorough motion test than the one using jerk assessment in the recording app.

The choice of features is based mainly on what has been attempted in related projects, see section II. Even though they have not been used in the same way as we intend to, they could still be relevant. In addition to acceleration, applied features include mean acceleration, standard deviation of acceleration, standard deviation of mean peak acceleration, mean jerk, mean step duration, skewness, kurtosis and standard deviation of the power spectral density (see [22] for how they are computed). Other features were also tested but not used due to low impact on the classification performance.

The feature selection was undertaken using *Recursive Feature Elimination (RFE)* being available through the Scikit-Learn Python framework [23]. This method starts with using all features and recursively removes the feature that contributes the least (i.e. has the lowest absolute weight) to the classification. This is repeated until the desired number of features remain. For our work, rather than deciding to use a specific number of features, the criterion of removing features as long as there is no drop in the classification accuracy was applied.

### *C. Machine Learning Algorithms*

Three different machine learning techniques have been applied for the classification of the collected data, including Decision Tree (DT), Support Vector Machines (SVM) and Multi–Layer Perceptron (MLP). One input was assigned to each feature being selected and computed from one recording at a time, see section IV-A1. The MLP training applied 10 hidden nodes, a learning rate of 0.1 and a momentum constant of 0.9. Details about the implementations can be found in [22].

## IV. Experiments

This section reports first on the data collected from users and then the performance of training classifiers for the two emotional dimensions.

### A. Data Collection from App Users

Participants for the data collection were found through one of the author's personal network. Out of 62 people asked, 22 accepted, see Table III. The rest either did not respond or did not use an Android phone. The 22 participants received instructions together with the application *Emotions* and confirmed that they were going to use it. However, only ten actually participated, and only three, the first author of this paper included, submitted more than 10 recordings. In total, 196 recordings[2] were collected.

TABLE III: Participants

| | |
|---|---|
| # asked: | 62 |
| # accepted: | 22 |
| # participated: | 10 |
| # recordings: | 196 |

TABLE IV: Participants

| | Low | Neutral | High |
|---|---|---|---|
| # Pleasantness: | 59 | 89 | 48 |
| # Arousal | 87 | 77 | 32 |

Table IV shows the distribution of classes for each of the two dimensions in the recordings. The *five* choices for each of the two dimensions collected where divided into *three* classes for each dimension. The main reason for doing that was to slightly increase the limited number of data for each class to be trained. Thus, each classifier would have three outputs, representing low, neutral and high, respectively.

TABLE V: Common classification details

| | |
|---|---|
| Classifiers | Decision tree (DT), support vector machines (SVM) and multilayer perceptron (MLP) |
| # runs of classifier | 200 (DT and SVM) / 10 (MLP) |
| Sampling rate | 50 Hz |
| Validation | K-fold cross-validation (K=5) |
| Comparison to random guess | With $M$ recordings total and $m$ recordings from the highest occurring class: $\frac{m}{M}$ |

*1) Feature Selection:* Experimental settings for each of the runs are summarized in Table V. Running the RFE algorithm gives us two sets of features; one used for the pleasantness dimension and one for the arousal dimension. Many features were relevant to classify for the arousal dimension (mean acceleration, standard deviation of acceleration, standard deviation of mean peak acceleration, mean jerk, mean step duration, skewness and kurtosis) while only one was found relevant for classifying pleasantness (standard deviation of the power spectral density). As mentioned above, the features are computed for each of the 20 seconds recordings.

[2]The initial number is higher, but these are the ones remaining after preprocessing has removed some recordings.

### B. Experimental Results

Table VI shows an overview of the different experiments undertaken including which machine learning algorithm that resulted in the best performance.

TABLE VI: Overview of the experiments and best results

| | Pleasantness | | Arousal | |
|---|---|---|---|---|
| Experiment | Accuracy | Classifier | Accuracy | Classifier |
| Base case (10 users) | 46.1% | SVM | 70.5% | MLP |
| Selected features (10 users) | 48.1% | MLP | 73.2% | SVM |
| Selected features (3 users) | 50.9% | MLP | 75.0% | SVM |

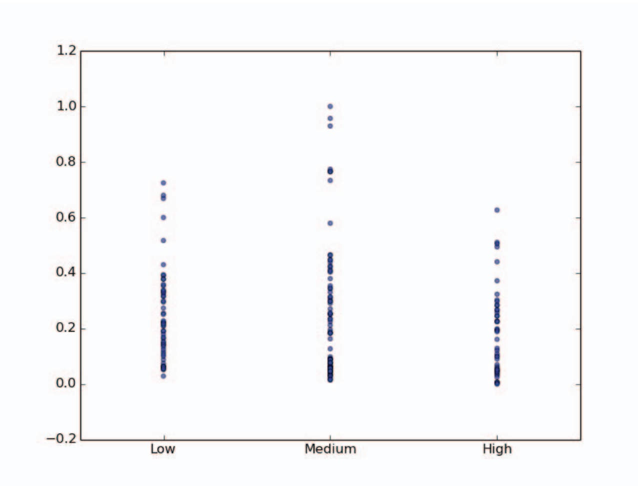
SVM and MLP performed alternately best and better than a decision three classifier. In the *base case*, only the mean and standard deviation of acceleration are used as features, and recordings from all 10 users are included. Classification using only those features establishes a base case where we only look at the energy of the movement. Intuitively, the energy should be connected to a person's state of activation/arousal, and therefore the accuracy for the arousal dimension is decent. The performance of the pleasantness dimension is not so high but still marginally better than random guess, which was 45.4% for 10 users and 46.2 % for 3 users, respectively. The performance increases somewhat when other and a larger number of features are applied (named *selected features* in the table).

The challenge of the classification is illustrated in Figure 2. In these scatter plots, the rescaled feature values calculated from each entry in the data set are plotted against the self-reported pleasantness and arousal, respectively. We see there is a limited distinction between the three classes, especially for the pleasantness dimension. Applying some of the other smartphones sensors for the pleasantness classification seem to be worth trying since only one of the many acceleration based features had an impact on distinguishing the classes and resulted in low classification accuracy.

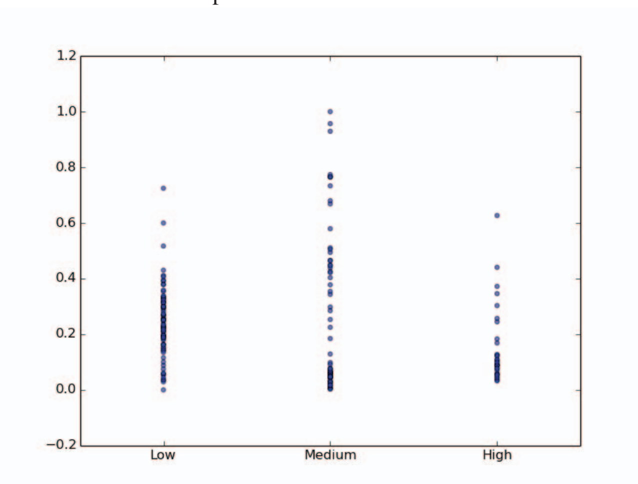
A separate experiment was undertaken using data from the three users having submitted 10 or more recordings. Slightly better performance was obtained compared to using data from 10 users (see bottom row in Table VI). The performance of the different classifiers for this experiment is included in Table VII. We see that the classification performance is relatively close for MLP and SVM and substantially higher than for DT.

TABLE VII: Performance of the experiments resulting in the best results

| | Pleasantness | | Arousal | |
|---|---|---|---|---|
| Algorithm | Accuracy | Std. Dev. | Accuracy | Std. Dev. |
| DT | 46.5% | 2.6 | 67.5% | 2.6 |
| SVM | 49.6% | 1.9 | **75.0%** | 1.6 |
| MLP | **50.9%** | 0.9 | 72.3% | 0.9 |




(a) Distribution of acceleration mean as a function of pleasantness.




(b) Distribution of acceleration mean as a function of arousal.

Fig. 2: Acceleration

## V. Conclusion

This paper has been concerned with classifying emotions over the two dimensions pleasantness and arousal, using accelerometer data from a smartphone carried in the participants' pocket during natural walking. A custom app has been developed and a method for feature extraction and classification of the collected data have been proposed. The results indicate that the arousal dimension can be predicted from such data, while the pleasantness dimension is much harder to predict. The best prediction rates achieved for arousal and pleasantness are 75.0% and 50.9%, respectively, for classifiers trained on data from all participants with at least ten recordings. Future work includes collection of more data from a larger number of participants as well as making attempts on detecting emotions from the phone while it is being used.

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